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A long-term and comprehensive assessment of the urbanization-induced impacts on vegetation net primary productivity

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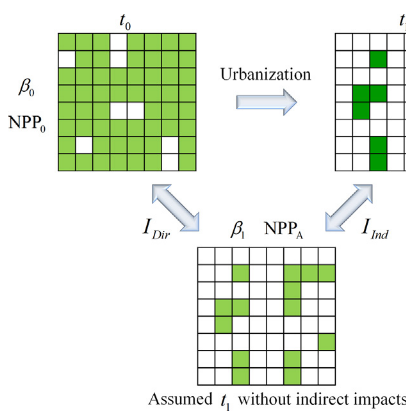
HIGHLIGHTS

- Urbanization decreases regional NPP due to the LUCC-induced direct impact.
- Enhanced by indirect impact, vegetation inner city grows better than in rural areas.
- Indirect impact promotes vegetation growth more in winter and in old city area.
- Urban heat island dominates the spatio-temporal distribution of indirect impact.

GRAPHICAL ABSTRACT



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ABSTRACT

Urbanization not only directly alters the regional ecosystem net primary productivity (NPP) through land-cover replacement, but it is also accompanied by huge indirect impacts due to the associated climate change and anthropogenic activities. However, to date, limited efforts have been made to quantitatively separate the two types of urbanization impacts, and the continuous variations over a long-time span are not well understood. In this study, both the long-term direct and indirect impacts of urbanization on NPP were established and analyzed based on multi-source remote sensing data, taking the city of Kunming in China as a case study area. The results indicated that the intense urbanization process has led to a continuous decrease in NPP from 1990 to 2014, due to the direct impact of land-cover replacement. Nevertheless, the urbanization has also resulted in an apparently positive indirect impact on NPP, which has offset about 30% of the direct impact in recent years. The increasing trend of the indirect impact was found to be higher than the NPP trend in the surrounding forest areas, which proves that vegetation growth has been promoted by the urban environment. The indirect impact has also shown great spatial and temporal heterogeneity, with generally higher values in the old city area and winter season. This can mostly be attributed to the distribution of temperature, i.e., the urban heat island effect, which has shown a significantly positive correlation with the indirect impact. However, the correlations between NPP and climatic factors were found to be completely different, which confirmed the need to separate the direct and

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indirect impacts. Overall, this study has demonstrated that urbanization has reduced the total NPP over the region, but has promoted some vegetation growth, and the knowledge of the indirect impact will help to support urban greening planning.

1. Introduction

Urbanization is a complex process involving population shift, land-cover changes, urban densification, high-rise buildings, and so on. The changes caused by urbanization can have a critical impact on the terrestrial ecosystem structure and functions, as well as the regional climate (Carreiro and Tripler, 2005; Gregg et al., 2003; Kalnay and Cai, 2003; Mckinney, 2002). Land-use/land-cover (LULC) change usually accompanies the urbanization process, which could not only happen within the inherent city region, but also sprawl to the nearby regions. For example, the replacement of vegetated areas and urban greening can directly alter the regional terrestrial ecosystem structure (Milesi et al., 2003; Yan et al., 2009; Yan et al., 2018). Furthermore, the vegetation growth environment, including the climate, soil texture, atmospheric conditions, and so on, are also seriously affected by urbanization. A typical example is the urban heat island (UHI) effect, which has been the subject of much concern (Gu et al., 2011; Gu et al., 2003; Zhou et al., 2016). The anthropogenic activities are also important aspects, because ecological management (e.g. irrigation, pruning, tree removal, etc.) can make a great contribution (Takagi and Gyokusen, 2004; Wu et al., 2014). All the above factors brought by urbanization can alter terrestrial ecosystems, especially the carbon budget (Pei et al., 2015; Wu et al., 2014). In past decades, the Earth has suffered rapid urbanization worldwide, which has become one of the most important components of global change (Vitousek et al., 2008; Yu et al., 2009). Under this background, it is necessary to advance our knowledge about the impact of urbanization on the terrestrial ecosystem carbon cycle (Churkina et al., 2010; Hardiman et al., 2017; Paolini et al., 2016).

Net primary productivity (NPP), which is the accumulated amount of organic matter produced by vegetation in a unit area in a unit time period, is an important ecological indicator that can be used to efficiently evaluate terrestrial ecosystem carbon budgets (Piao et al., 2005; Potter et al., 2003; Potter et al., 1993). NPP has been widely applied to the monitoring of the status of carbon cycles in different regions at different scales (Ciais et al., 2005; Fang et al., 2001b; Nemani et al., 2003; Piao et al., 2006). Different from vegetation index (VI), NPP quantifies the growth of vegetation over a specific time period, which relates to both the amount of vegetation and the growth environment in the region. It is also common to assess urbanization process impacts on a terrestrial ecosystem using NPP as the indicator, based on the remote sensing method (He et al., 2017; Peng et al., 2015; Taelman et al., 2016; Zhang et al., 2012). Due to the fact that field measurements are usually used for precise site research, and are difficult to obtain in urban regions, model estimation is a convenient way to obtain NPP in urban studies. With the development of satellite remote sensing, comprehensive land-surface information can be continuously captured in any area (Cramer et al., 1999; Field et al., 1995). In order to analyze the impact of urbanization on NPP over the past decades, a long-term NPP time series with high temporal resolution is needed. Besides, an adequate spatial resolution is also necessary to capture the spatial patterns in urban areas, which could show complex land contexture within a small region. However, limited by the sensor characteristics, none of the current remote sensing datasets can meet the above demands (Chen, 1999; Shen et al., 2016a; Yan et al., 2018). This has prevented further analysis of the NPP spatial distribution and temporal variation (Cheng et al., 2016; Shen et al., 2013). Thus, it is of great importance to obtain long-term NPP time series with an adequate spatial resolution, in order to advance the studies of urbanization (Gan et al., 2014; Liu et al., 2016; Shen et al., 2016b). The fusion of multi-source remote sensing data is an efficient way to solve this issue, and has been widely applied in many vegetation and other environmental studies (Hilker et al., 2009; Meng et al., 2013; Schmidt et al., 2012; Shen et al., 2016a). The fusion method can synthesize the respective advantages of different sensors, and break the limitations of the individual datasets (Guan et al., 2017).

Numerous researchers have investigated the impact of urbanization on NPP in different cities at different scales, and many different conclusions have been reached (Milesi et al., 2003; Pei et al., 2013; Wu et al., 2014; Yu et al., 2009). For a single city, Yu et al. (2009) declared that a move toward urban landscape change in the city of Shenzhen caused NPP loss totaling 321.51 Gg of carbon; Liu et al. (2018) showed that the conversion from cropland to built-up area led to approximately 309.95 Gg C loss over 13 years in Wuhan. For multiple cities over a large region, Pei et al. (2013) found that urban land development has had an overall negative effect on the terrestrial NPP in the cities of China; and Imhoff et al. (2004) indicated that urbanization in the United States has reduced the amount of carbon fixed through photosynthesis by 1.6% of the pre-urban input. It can be concluded that many of the previous studies have focused on the negative impact of the land-cover replacement on NPP, and the impacts of other factors have not been addressed. However, some researchers have indicated that vegetation growth has been evidently enhanced in the urban environment, due to the UHI effect, the longer growth period, anthropogenic activities, and so on (Gu et al., 2003; Takagi and Gyokusen, 2004; Zhao et al., 2016; Zhou et al., 2016). Zhao et al. (2016) used the Moderate Resolution Imaging Spectroradiometer (MODIS) MOD13A2 enhanced vegetation index (EVI) products as an indicator. They defined the direct impact as the LULC effect of urbanization, and the indirect impact was regarded as the influence of other factors, such as climate change, anthropogenic activities, and so on. It was found that the vegetation growth of most cities in China is clearly improved by the indirect impact, which offsets about 40% of the direct loss caused by the direct impact. However, few studies have explored both the direct and indirect impacts of urbanization on regional NPP, and a systematic understanding of the effect of urbanization on regional carbon budgets is lacking. What is more, most of the previous studies have only analyzed the NPP differences between two selected time points, as the status before and after urbanization (Chen et al., 2017; Li et al., 2016; Tian and Qiao, 2014; Wu et al., 2014; Yang et al., 2014). Knowledge of the variation in each year during the two time points is lacking, but the continuous long-term change of urban carbon budgets is worth investigating. Time series of the impact of urbanization on NPP have seldom been obtained, but are important for a detailed evolution analysis, and could help to clarify the relationship with climate change or other factors. Overall, the knowledge of the impact of urbanization on vegetation NPP needs to be further advanced. In particular, efforts should be made to separate the different impacts and obtain continuous time series.

The city of Kunming in China was selected as the case study area. Kunming is the capital of Yunnan province, and is one of the largest metropolises in southwestern China. The city is an important gateway to Southeast Asia, and is considered to be one of the most livable cities in China. However, Kunming has suffered from rapid urbanization over the last few decades, with an expanding urban area and population (Zhu and Yang, 2013). A number of studies have investigated the change of the UHI effect in the region, but the impact of urbanization

on the regional ecological environment has not been investigated in an in-depth way (Wang et al., 2010; Zhang et al., 2002). The urbanization has had a huge effect on the regional carbon budget, and has even affected the whole of Yunnan province, which is one of the most important carbon sinks in China (Fang et al., 2001a). Thus, it is important to further investigate the impact of urbanization in Kunming on NPP. Our previous studies of Yunnan province could provide us with available NPP datasets from 1982 to 2014 at a 1-km scale, to fulfill the necessary requirements of time span and spatial resolution (Guan et al., 2017).

To address these issues, the main objectives of this paper are: 1) to efficiently separate the direct and indirect impacts of urbanization in Kunming on NPP in recent decades; 2) to discuss the spatio-temporal variation of the different impacts, as well as their driving mechanisms; and 3) to evaluate the carbon loss caused by urbanization, and to provide suggestions as to how to mitigate this loss. The long-term NPP series and land cover data with different spatial resolution are utilized to obtain the direct and indirect impacts of urbanization from 1990 to 2014, based on the concept that NPP of an urban pixel is determined by the fraction of vegetated surface. Four different parts within or around the urban region are defined to cognize the variation and distribution of these two impacts. Based on it, the best planning for urban greening can be formulated, considering the impacts of urban environment. What is more, the relationship between indirect impact and climatic factors are further analyzed, in order to clarify the driving factor of the impact on NPP.

2. Materials and methods

2.1. Study area

The city of Kunming (24.38°N–26.36°N, 102.17°E–103.67°E) is located in north-central Yunnan province, which is the most southwestern province of China with high forest coverage, as shown in Fig. 1. The city covers a total area of 21,473 km^2, with a mean elevation of 1891 m, and is surrounded by mountains on three sides. It is located in the northern subtropical monsoonal climate zone, which is characterized by abundant precipitation and moderate temperatures (He et al., 2002). However, the climate shows great seasonal heterogeneity, with wet summers and dry winters, and most of the precipitation takes place in the growing season (from May to October). Severe droughts in Yunnan, such as the droughts in 2005 and 2009, have greatly impacted the ecosystem in the city (Abbas et al., 2014; Liu et al., 2014). The city of Kunming has also experienced high-speed urbanization over the last 30 years, especially since the late 1980s, which has led to an obvious increase in the UHI intensity (Wang et al., 2010; Zhang et al., 2002). In order to distinguish the spatial patterns of the urbanization impacts, the total urban area (TA, the city range after urbanization in 2014) was divided into old city (OC, the city range before urbanization in 1989) and expansion area (EA, the difference of the city range from 1989 to 2014). The city range in each year was obtained from the land-cover data, as the morphological operation results of impervious surface (Shen et al., 2016a). In addition, the sub-urban area (SA, a 5-km buffer region of the TA) and non-urban area (NA, a mountain forest region near the city with the same size as the TA) were defined to compare with the conditions in the urban area.

2.2. Data sources

2.2.1. The 1-km NPP data from 1982 to 2014

In order to meet the requirements of a long-term urban vegetation study, we employed the 1-km NPP time series for 1982 to 2014 from our previous study (Guan et al., 2017). The data was estimated by fusing multi-source remote sensing data and observed meteorological and radiation data, based on the Carnegie-Ames-Stanford Approach (CASA) model. In the NPP estimation framework, two normalized differential vegetation index (NDVI) products were employed to composite a new NDVI time series, combining the respective advantages of time span and spatial resolution. The products used were the Advanced Very High Resolution Radiometer (AVHRR) Global Inventory Modelling and Mapping Studies 3rd generation (GIMMS3g) product from 1982 to 2012 with an 8-km resolution, and the MODIS MOD13A3 data collection from 2000 to 2014 with a 1-km resolution (Gan et al., 2014; Liu et al., 2015; Yang et al., 2015). The obtained NPP time series showed good consistency with the field measurements ($r = 0.79$), which is much higher than the NPP calculated from the original NDVI data (Guan et al., 2017). Thus, the NPP time series can be deemed as suitable for the ecosystem analysis and for the investigation of the impact of urbanization on NPP, because of its superior spatial resolution and time span. The NPP data can be freely downloaded from (http://rs-pop.whu.edu.cn).

2.2.2. The urban expansion intensity data

The Landsat Thematic Mapper (TM)/Enhanced Thematic Mapper Plus (ETM+)/Operational Land Imager (OLI) images were applied to classify the land cover in the city of Kunming at a spatial resolution of 30 m, covering the time period from 1987 to 2014. The urban impervious surface is a land-cover type that prevents the ingress of water, and includes roads, parking lots, building roofs, and so on. The identification

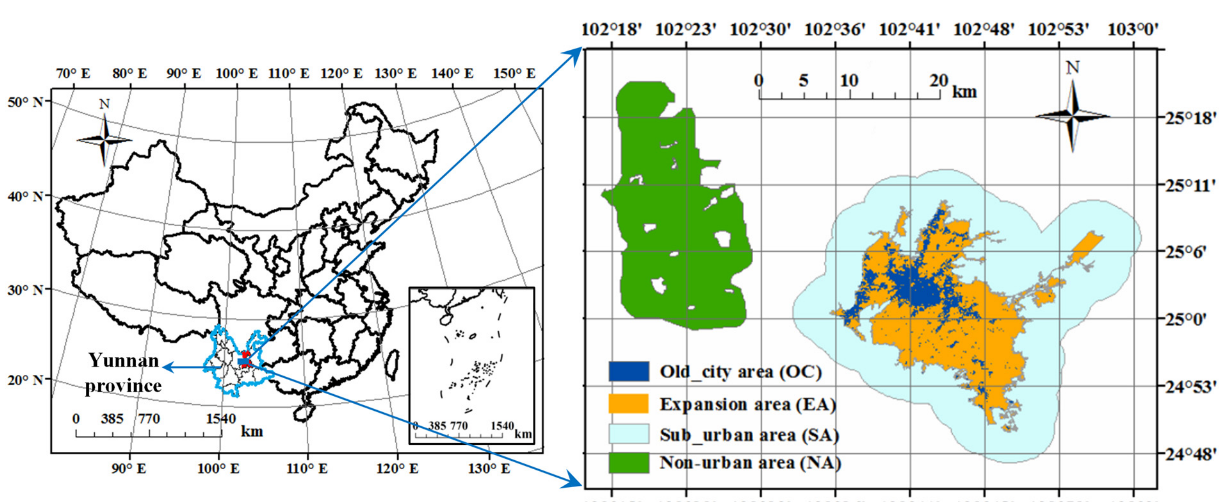

Fig. 1. The location of the study area.

of the urban impervious surface land-cover type has been widely applied to represent the development and expansion of cities. Thus, in this study, the region was classified into three land-cover types: vegetation, impervious surface, and bare soil. The maximum likelihood classification method was applied to the data after the processes of radiometric calibration and atmospheric correction. The water bodies were eliminated using the modified normalized difference water index (MNDWI), which could efficiently identify water bodies in urban area using the green and mid-infrared bands (Xu, 2006; Du et al., 2016). The additional validation samples were carefully selected from the original images and Google Earth images from 2011, and the confusion matrix indicated that the overall accuracy of the classification results was higher than 90%. Based on the classification results, the urban expansion intensity of the city could be quantified using the percentage of impervious surface in a single pixel (Zhao et al., 2016). By utilizing the spatial resolution differences of the NPP data and land-cover data, the number of impervious pixels in each NPP pixel could be calculated, and thus a time series of the urban expansion intensity over the past decades was obtained. Furthermore, morphological processes were conducted with the binary impervious surface data, to extract the urban ranges before and after urbanization. In order to ensure that the urban expansion intensity in each year was representative, the Landsat images selected for the classification were all chosen around the spring season, so the time intervals for each year were as close as possible. The details of the Landsat images used for each year are provided in Table S1.

2.3. Methods

Urbanization can have many different impacts on regional ecosystems, including vegetation replacement, urban greening, the UHI effect, artificial irrigation, pruning, and so on. Among these impacts, the land-cover replacement is the direct impact, which directly alters the amount of vegetation and is always negative for urbanization. Climate change and the anthropogenic factors contribute to the growth status of vegetation, and together lead to the indirect impact. The indirect impact can help us to evaluate the contribution of urbanization to the regional ecosystem. Zhao et al. (2016) developed a framework that can identify the direct and indirect impacts of urbanization on the EVI, based on the concept that the EVI of an urban pixel can be decomposed into contributions from vegetation and non-vegetated surfaces. However, the framework can only obtain the urbanization impacts from a specific time point to the initial time point with full vegetation cover, and the continuous variation during a time period is not supported.

In order to obtain both the direct and indirect impacts of urbanization on NPP in any year, an improved method is proposed in this paper, assuming that the NPP of an urban pixel is determined by the fraction of vegetated surface. The overall concepts are shown in Fig. S1, and are described in detail in the following:

$$NPP(x,t) = [1-\beta(x,t)] \times NPP_{FV}(x,t)$$

where $NPP(x,t)$ is the NPP in pixel x at time t; $\beta(x,t)$ is the urban expansion intensity; and $NPP_{FV}(x,t)$ is the NPP value of pixel x when it has full vegetation cover. Thus, based on this concept, we can obtain the direct and indirect impacts of urbanization on NPP. Assuming that there is no indirect impact on the vegetation during the urbanization period from t_0 to t_1, the hypothetical NPP_h after urbanization in t_1 can be expressed as:

$$NPP_h(x,t_1) = NPP(x,t_0) + [\beta(x,t_0)-\beta(x,t_1)] \times NPP_{FV}(x,t_0)$$

where $NPP(x,t_0)$ is the NPP value in pixel x before urbanization in time t_0; β_0 and β_1 are the urbanization intensities in t_0 and t_1; and NPP_{FV0} is the NPP value of the full vegetation cover pixel before urbanization. Since there are no other impacts on the vegetation growth, the change of NPP between the two times should just be the difference of the vegetated area, which can be evaluated by the urban expansion intensity. Based on the NPP_h in t_1, we can calculate the direct impact I_{Dir} and indirect impact I_{Ind} of urbanization on NPP as follows:

$$I_{Dir}(x,t_1) = NPP_h(x,t_1)-NPP(x,t_0)$$

$$I_{Ind}(x,t_1) = NPP(x,t_1)-NPP_h(x,t_1)$$

where $NPP(x,t_1)$ is the true NPP after urbanization in time t_1. As $NPP_h(x,t_1)$ is the hypothetical NPP value after urbanization, just considering the direct impact of land-cover changes, the difference between $NPP_h(x,t_1)$ and the NPP at t_0 should be the direct impact of urbanization on NPP during the period. Furthermore, the difference between $NPP_h(x,t_1)$ and the true NPP at t_1 should be the indirect impact. In this study, the year of 1989 was set as t_0, which means the time before urbanization, because the urban expansion intensity from 1987 to 1989 changed very little. Furthermore, the mean NPP value from 1982 to 1989 was regarded as the NPP_0 value, to ensure it could represent the vegetation status before urbanization, and was not affected by the abnormal changes in a unique year. According to this concept, we could calculate the direct and indirect impacts of urbanization on NPP in every year from 1990 to 2014, based on the NPP and the urban expansion intensity time series. It was indicated that the government has banned deforestation around the region from a very early date, so the logging and thinning would be very slight and most of the land cover change could be detected using satellite images at the resolution of 30 m.

3. Results

In Section 3.1, the urbanization processes in the city of Kunming are first studied using the percentage of impervious surface. The NPP levels in the different regions are then compared in Section 3.2, in order to distinguish the overall impact of urbanization on urban NPP. The direct and indirect impacts are analyzed in Section 3.3, including the inter-annual variation, the spatial difference, and the seasonal heterogeneity. In Section 3.4, the correlation between the indirect impact and climatic factors is discussed, to clarify the generation mechanism of the indirect impact.

3.1. Urbanization of the city of Kunming over the last 25 years

3.1.1. Inter-annual variation of each land-cover type

As shown in Fig. 2, the percentage of impervious surface, which represents the urban expansion intensity of the city of Kunming, has continuously increased since 1990, but has shown a decrease in the last

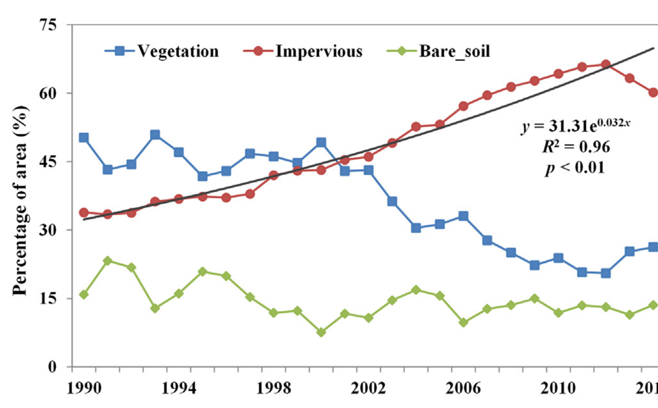

Fig. 2. Inter-annual variation of the percentage of the three land-cover types.

two years of the study period. After examining different fitting models (e.g. linear, polynomial, exponential, logarithmic), an exponential regression was found to be the best fit for the annual variation of impervious surface ($R^2 = 0.98$, $p < 0.01$), which indicates that the region has suffered from intense urbanization at an accelerating rate. The city expanded the fastest during the period from 2003 to 2012, when the impervious surface percentage was above the exponential fitting line. However, the urban sprawl has slowed down since 2010, and the impervious surface has even reduced since 2013 after the peak in 2012. The impervious surface occupied about 33.47% of the region originally, but the percentage had doubled (66.30%) by 2012. In contrast, the percentages of vegetation and bare soil areas have decreased along with the urbanization, but the rate has slowed down since 2008. As a result, the vegetation coverage was about 50.28% in the study area before the urbanization, and the percentage had declined to 20.57% by 2012. It can also be observed that there was an increase of the vegetation fraction after 2012, which suggests that urban greening has taken place in the last two years of the study period. This may be because the regional government has paid more attention to the urban ecological environment since 2012, and corresponding regulations were implemented in March 2012. Thus, an increase in vegetation cover and a decrease in impervious surface was found in the last two years, because intense urban greening was conducted by the government to improve the city environment.

3.1.2. Conversion of each land-cover type

The conversion of the different land-cover types over the last 25 years was further investigated. The spatial locations and statistics of the six land-cover change types are summarized in the following. As shown in Fig. 3, it can be observed that large areas (59.12%) in the city of Kunming have been subject to land-cover changes. Only about 40.88% of the area has maintained the same land cover from 1989 to 2014, and more than half of this is the initial impervious surface area. The blue colors, which represent the impervious surface increments, cover 37.68% of the city area, and indicate the drastic urbanization that has taken place in the region. Among the changes, 54.95% of the changes to impervious surface have been converted from vegetation, amounting to 20.7% of the city area. However, the urban greening, as demonstrated by the green color, has only occurred in 14.95% of the region, and most of this was in the city parks or the mountainous regions around the city fringe. Overall, this means that the urbanization process has decreased the vegetated area, which will have had a direct negative impact on the ecosystem structure and function. Furthermore, most of the OC region (71.71%) has maintained the same land cover after the urbanization, because impervious surface already covered most of this area before the urbanization. Among the areas with no land-cover change, 96.93% are impervious surface. The impervious surface increase was only 7.25% in the OC area, but the urban greening amounted to 15.57%. This indicates that there was only light construction in the OC area, but obvious urban greening has taken place, which is different from the condition in the EA area. In general, these changes indicate that the region has suffered from intense urbanization, which has had a great impact on the terrestrial ecosystem structure with huge heterogeneity.

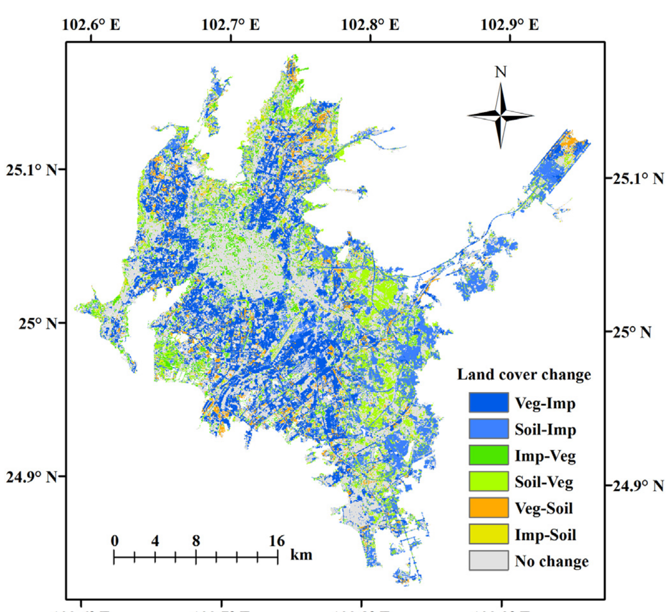

Fig. 3. Spatial distribution of the different land-cover change types from 1989 to 2014 in the city of Kunming area. Imp means impervious surface. Veg means vegetation cover. Soil means bare soil. Veg-Imp means land cover that has changed from vegetation to impervious surface, and the other five land-cover change types are depicted in the same way.

3.2. NPP spatial differences caused by urbanization

In order to assess the impact of urbanization on NPP, the inter-annual variation of the NPP in the OC, EA, SA, and NA regions is shown in Fig. 4. Overall, this indicates that the annual NPP of the four different regions has showed different variation trends over the last 25 years. There has been a decrease in NPP in the OC, EA, and SA regions, but increased NPP can be found in the NA region (1.34 $gC\cdot m^{-2}$ per year). Furthermore, the fluctuations of the NPP in each year are very similar for the four regions, and differences only exist in the variation trends. The NA region is near the city area and has remained forested over the study period, so its NPP variation can thus represent an area that has not been impacted by urbanization. Thus, if there was no urbanization process in the urban region, its NPP variation should be the same as the trend in the NA region. However, impacted by the urbanization process, the NPP levels of the three urban regions have all showed decreasing trends with different speeds. This means that the urbanization has had an apparently negative influence on the regional terrestrial ecosystem carbon cycle. Furthermore, the rates of decrease in the three regions have also shown huge differences. The NPP in the EA region has declined the fastest, at a rate of -9.83 $gC\cdot m^{-2}$ per year, and the rate in the SA region has been the slowest, at -1.19 $gC\cdot m^{-2}$ per year. The rate of decrease represents the urban expansion intensity. The EA region has unquestionably shown the highest rate of urban expansion intensity increase and the greatest NPP decline, and the urban expansion intensity change in the SA region has been less than that in the OC region. Overall, the urbanization has clearly reduced the NPP in the urban

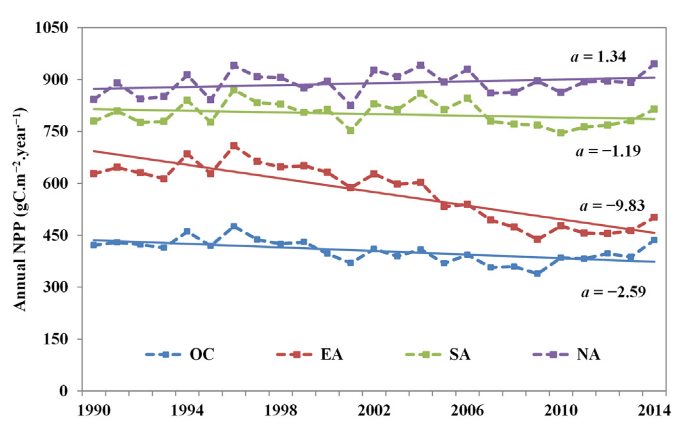

Fig. 4. Inter-annual variation of the NPP in the old city (OC), expansion area (EA), suburban area (SA), and non-urban area (NA), where *a* denotes the variation trends of NPP.

area, and the spatial distribution of the change is closely related to the urban expansion intensity variation.

3.3. Direct and indirect impacts of urbanization on NPP

3.3.1. Overall variation

Although the urbanization in Kunming has reduced the urban NPP, this is the result of the direct impact caused by land-cover replacement, which led to the decrease of the vegetated area. However, the indirect impact of climate change and anthropogenic activities can also greatly alter the ecosystem carbon cycle. As shown in Fig. 5, the direct and indirect impacts have been separated, and their inter-annual variations are compared. It can be observed that the direct impact of urbanization on NPP is clearly negative, and the negative impact has grown with the process of urban sprawl. The NPP loss caused by the direct impact of urbanization reached a peak of 233.45 $gC\cdot m^{-2}\cdot year^{-1}$ in 2012, and then dropped to 200.45 $gC\cdot m^{-2}\cdot year^{-1}$ after the urban greening in 2013 and 2014. This indicates that the regional ecosystem carbon losses could have reached as much as 233.45 g per unit area per year after the urbanization, due to the land-cover changes. In contrast, after removing the impact of land-cover replacement, we can observe that the positive indirect impact has shown an increasing trend during the urbanization process. Although the inter-annual variation has fluctuated, the indirect impact was above zero in almost all the years, and has shown a logarithmically increasing trend over the last 25 years (the best fit model, $R^2 = 0.27$, $p < 0.05$). This means that the urbanization has promoted vegetation growth, ignoring the impact of the reduced vegetated area, and this promotion increased with the process of urbanization. The logarithmically increasing trend indicates that the increasing rate of the indirect impact was obvious before 2000, but slowed down after this date, and may remain stable in the future. This is because the influence of the indirect factor has reached saturation, including the natural and urbanization-induced climate change, anthropogenic activities, and so on. With the advance of the urbanization process, the evolution of these factors could enhance vegetation photosynthesis more and more at the beginning, but this eventually reached a bottleneck. For the last five years, on average, the indirect impact could offset 30.12% of the NPP loss caused by the direct impact of land-cover change. What is more, the indirect impact was also abnormal in some years with extreme climate phenomena, such as the very low values in 2005 and 2009 caused by the extreme droughts. Overall, the urbanization has reduced the regional NPP, mainly due to the replacement of vegetation, but it has also resulted in a significant positive indirect impact on vegetation growth, which has shown a logarithmically increasing trend.

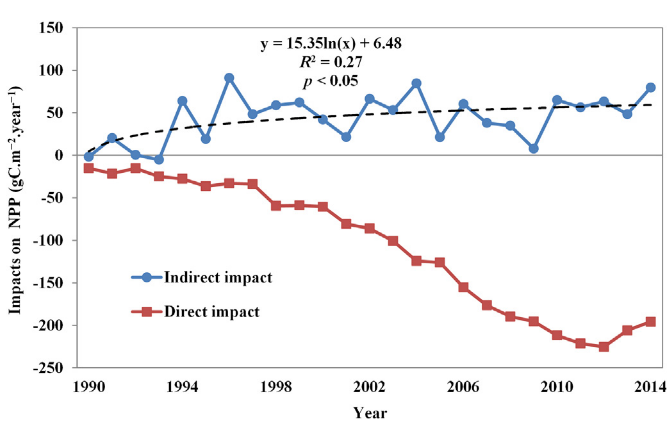

Fig. 5. Inter-annual variation of the direct and indirect impacts of urbanization on NPP.

3.3.2. Spatial differences

Urbanization has shown a positive indirect impact and a negative direct impact on NPP in most of the urban area. In order to establish the spatial differences of the urbanization impacts on NPP, the statistics of the direct and indirect impacts in the different regions were further calculated, as shown in Table 1. It can be observed that the direct land-cover replacement has affected the NPP in the EA region the most, with the direct impact more than double that of the OC area. This can be considered a reasonable result, because the vegetation percentage loss should be the highest in the EA region, and is lower in the other region. In contrast, the indirect impact in the OC region is the highest, and the value in the SA region is much lower than in the other two urban regions. This indicates that the urbanization process has promoted the vegetation growth in the urban area, including the OC and EA regions. We also calculated the linear trends of the annual direct and indirect impacts in the different regions. As shown in Table 1, the spatial distribution of the direct impact variation trends agrees with its value, which is highest in the EA area and much less in the other two regions. For the indirect impact, the mean trend value is 1.55 $gC\cdot m^{-2}$ per year, which is higher than the increasing trend of NPP in the NA area (1.34 $gC\cdot m^{-2}$ per year). This indicates that the NPP under natural environments has increased slower than the NPP impacted by the urbanization, which reveals an interesting finding, in that the vegetation has actually been growing faster in the urban region than in the natural environments. This further proves that urbanization has brought many positive factors to the Kunming region that can enhance the vegetation growth. The urban heat/rain island effect, anthropogenic activities, and other favorable factors caused by urbanization are the main positive factors, which result in a much more suitable growing environment and benefit vegetation photosynthesis. What is more, the spatial heterogeneity of the indirect impact trend also agrees with the distribution of these positive factors. In the OC region, where the heat island intensity is the strongest, the indirect impact shows the highest value. The indirect impact trend in the SA region is very similar to the NPP trend in the NA region, because there is no heat island phenomenon in this region. Thus, it can be concluded that the urbanization has led to an obviously positive impact on vegetation, because the induced UHI effect and other factors can greatly benefit photosynthesis.

3.3.3. Seasonal heterogeneity

The impacts of urbanization on NPP also show huge seasonal heterogeneity. The seasonal distribution of the direct impact completely agrees with NPP, because the direct impact is caused by the replacement of the vegetated areas, which would maintain a stable percentage for different seasons. However, this is completely different for the indirect impact, which shows great seasonal heterogeneity, as shown in Fig. 6 (a). Overall, the indirect impact in the winter months is higher than in the summer months. The lowest value is observed in the summer months with the highest temperatures, and the highest value appears in the months with the greatest temperature change (March and September). Due to the difference in the NPP amount in each month, the ratio of the indirect impact and NPP is a more effective index to evaluate the seasonal heterogeneity, which we name the percentage of indirect impact (PII). The PII shows an obvious U-shaped intra-annual variation, with high values in winter and low values in summer. This means that the indirect change caused by urbanization promotes the vegetation growth more in the colder months, but is limited in the warmer months. The seasonal variation of temperature is the reason for this, because the higher temperature brought by the UHI effect benefits the vegetation more when the temperature is the main limiting factor for growth in the winter months. Nevertheless, the temperature in summer is usually quite suitable for vegetation photosynthesis, so the extra warming does not further promote the NPP. What is more, the PII in the OC and EA regions was also calculated, but the SA region was not included because it was established that there has been little vegetation promotion in this region. The PII in the OC region is usually higher than that in the EA

Table 1
Annual variation trends of the direct and indirect impacts on NPP in the different regions.

	Impact	TA	OC	EA	SA	NA
Mean value in 2010–2014	Direct impact	−212.05	−99.49	−238.26	−56.58	/
($gC \cdot m^{-2} \cdot year^{-1}$)	Indirect impact	62.66	66.37	61.79	19.21	45.77
Variation trend	Direct impact	−10.03	−4.28	−11.37	−2.46	/
($gC \cdot m^{-2} \cdot year^{-1}$)	Indirect impact	1.55	1.62	1.53	1.30	1.34

Note: TA denotes the total city area, OC denotes the old city area, and EA denotes the expansion area, SA denotes the sub-urban area, and NA denotes the non-urban area.

region, except for July and August. This indicates that the vegetation in the OC region benefits more than that in the EA region, for most of the time, except for the two months with the highest temperature. This is likely a result of the UHI intensity in the OC region being greater than that in the EA region, which has been proved in many studies (Shen et al., 2016a). Therefore, the indirect impact can promote NPP more in the OC region, most of the time, but a negative impact occurs when the monthly temperature is originally high. Thus, the NPP promotion brought by the indirect impact is generally higher in the winter months than the summer months, which is a result of the spatio-temporal distribution of temperature and UHI intensity.

3.4. Relationship between climate and the indirect impact

The direct impact is the result of vegetated area replacement, but the reasons for the indirect impact of urbanization on NPP have not yet been clarified. In order to quantitatively describe this issue, the correlation coefficients of the indirect impact and climatic factors in different time periods and different regions were calculated and are shown in Table 2. For the entire period from 1990 to 2014, the indirect impact has shown a significant positive correlation with temperature ($r = 0.44$, $p < 0.05$), but no significant relationship can be found for precipitation, which means that the temperature is the main driving force for the indirect impact. Furthermore, according to the inter-annual variation of the indirect impact, it apparently increased with the urban sprawl from 1990 to 1999, but fluctuated at a relatively stable level after 2000. Thus, the relationships between the indirect impact and climatic factors were further analyzed in these two periods. In the first time period from 1990 to 1999, when the indirect impact apparently increased, the temperature showed an even higher correlation with the indirect impact ($r = 0.70$, $p < 0.05$). However, the correlation became very low in the second period after 2000, when the urban expansion intensity was already high. Thus, it can be concluded that the higher temperature caused by urbanization (both natural climate change and the UHI effect) was the main factor responsible for the positive indirect impact on NPP. In the first 10 years, the temperature persistently increased and enhanced the NPP, so the indirect impact grew with the urbanization process. Whereas, when the urban temperature was already suitable for vegetation growth, even the intense UHI effect could not further benefit the vegetation growth, which remained at a relatively stable level after this period.

For the correlations in the OC and EA regions, spatial differences can also be found. The correlation between temperature and the indirect impact is higher in the EA region than in the OC region, both over the entire period and in the first period. This could be a result of the higher UHI intensity in the OC region, which means that the temperature in the old city was originally high and was usually higher than that in the EA region at the same time. Therefore, the climate condition in the OC region was years ahead of that in the EA region, so the temperature increment benefited the vegetation less in the OC region with lower correlation coefficient, especially in the first period before 2000. In general, the temperature was the major driving force for the growing positive indirect impact, but their correlation was weakened during the urbanization process, with generally higher values in the EA region.

4. Discussion

Urbanization can have a huge influence on the terrestrial ecosystem. In this study, the direct and indirect impacts of urbanization on NPP were separated and analyzed. Although a number of conclusions could be drawn, some issues still need to be further discussed. In this section, the necessity of separating these two impacts is first established. How to offset the impacts of urbanization on the regional carbon budget is then explored, considering the huge heterogeneity of the indirect impact. Finally, the quality/uncertainty of the data applied in this study is discussed, and some potential directions for future study are described.

4.1. Necessity of separating the impacts of urbanization on NPP

Most of the previous studies about the impact of urbanization on vegetation have only concentrated on the gross influence, and they have not identified the direct and indirect impacts. If the indirect impact was not considered in the city of Kunming, we could only make the conclusion that urbanization has reduced the urban NPP over the last 25 years, as shown in Fig. 4. However, in fact, although the urban NPP decreased with the urbanization, the vegetation growth was promoted during the process. The reduced NPP was the result of more than half the area of vegetation being replaced over the past 25 years, but the

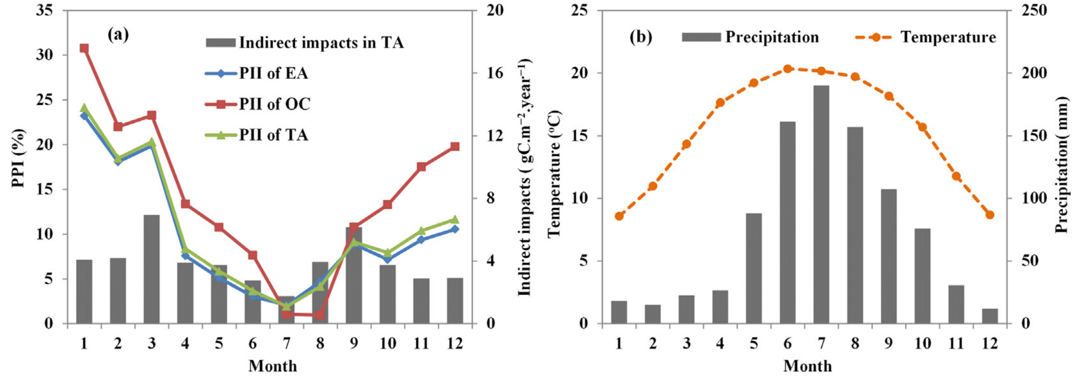

Fig. 6. Intra-annual variation of: (a) urbanization impact on NPP; and (b) climatic factors.

Table 2
Correlation coefficients between the indirect impact and climatic factors in different time periods and different regions.

Region	R	1990–2014	1990–1999	2000–2014
TA	r_P	0.061	0.38	−0.06
	r_T	0.44*	0.70*	0.014
OC	r_P	−0.19	0.23	−0.45
	r_T	0.43*	0.59	0.17
EA	r_P	0.11	0.41	0.039
	r_T	0.45*	0.72*	0.054

Note: TA denotes the total city area, OC denotes the old city area, and EA denotes the expansion area; r_P denotes the correlation between the indirect impact and precipitation, and r_T denotes the correlation between the indirect impact and temperature; * denotes a significant correlation ($p < 0.05$).

remaining vegetation was much more productive after the urbanization. The indirect impact also increased along with the urbanization process, and its trend was greater than the increasing trend of the NPP in the NA region near the city. The difference reached 0.25 $gC \cdot m^{-2}$ per year, which indicates that the positive impact of urbanization can help vegetation produce an extra 0.25 gC in each year in one square meter. The anthropogenic influences and the urbanization-induced climate change are the main reasons for the positive indirect impact. For example, artificial irrigation, pruning, the UHI effect, and so on, can result in superior conditions in the urban region. All these conclusions could only be made by separating the direct and indirect impacts of urbanization on NPP, and the identification of the two impacts can help us to recognize the deep relationship between urbanization and ecosystems.

Furthermore, separating the impacts of urbanization on NPP can also help us to identify the real relationship between NPP and climatic factors. Due to the presence of the direct impact, the overall urban NPP variation cannot represent the vegetation status in the region, because even though the vegetation growth is promoted, the regional NPP is decreased due to the reduced vegetated area. In this case, directly calculating the correlation between urban NPP and the climatic factor cannot reflect the true relationship between them. Table 3 shows the correlation between NPP and the climatic factors in different time periods and different regions. It can be concluded that precipitation is the main factor influencing the urban vegetation variation, and there is a negative relationship with temperature. Compared to the information of the indirect impact in Table 2, completely opposite conclusions can be reached. The conclusions obtained from the NPP would, however, be wrong, because the close correlation with precipitation is the result of their decreasing trends. However, it was found that the vegetation has grown much better with the process of urbanization, and the lower urban NPP was just because of the reduced productive area. Therefore, the positive relationship between NPP and precipitation would a wrong answer, which would not reflect the true climatic driving mechanisms for urban vegetation. Actually, it is the temperature that has dominated the vegetation growth status in the Kunming urban area, which is a conclusion that could only be made by considering the indirect impact. Thus, it is necessary to separate the direct and indirect impacts of urbanization on NPP, in order to discover the true relationship between urbanization and the urban ecosystem.

Table 3
Correlation coefficients between NPP and climatic factors in different time periods and different regions.

Region	r	1990–2014	1990–1999	2000–2014
TA	r_P	0.55*	0.17	0.59*
	r_T	−0.41*	0.33	−0.34
OC	r_P	0.34	0.07	0.14
	r_T	−0.21	0.21	0.14
EA	r_P	0.56*	0.19	0.60*
	r_T	−0.42*	0.34	−0.36

Note: TA denotes the total city area, OC denotes the old city area, and EA denotes the expansion area; r_P denotes the correlation between the indirect impact and precipitation, and r_T denotes the correlation between the indirect impact and temperature; * denotes a significant correlation ($p < 0.05$).

4.2. How to offset the impacts of urbanization on the regional carbon budget

Due to the land-cover change and climate change, urbanization leads to changes of the local ecosystem carbon budget. The total NPP (T-NPP), which denotes the sum of the pixel NPP multiplied by the pixel area in the region, is used to represent the regional carbon budget. The average NPP in the last 8 years is used as the NPP value after urbanization, to weaken the impact of the abnormal variations in some years, and keep the same as the NPP before urbanization. As shown in Fig. 7, the urbanization has led to an obvious carbon sink loss in the past decades, at a rate of 0.088 $TgC \cdot year^{-1}$. Among the different regions, the EA region contributed the most, with a loss of 67.03% (0.059 $TgC \cdot year^{-1}$), and the change in the OC region was the lowest (4.43%, 0.0039 $TgC \cdot year^{-1}$). This was mostly due to the replacement of the vegetated area, and the low value in the OC region can be attributed to the highly promoted vegetation growth. The actual NPP of the full vegetation cover area (NPP-FV), which denotes the genuine status of the vegetation growth, showed the greatest increment in the OC region, at a rate of 391.91 $gC \cdot m^{-2} \cdot year^{-1}$. The increments of NPP-FV were 255.24 $gC \cdot m^{-2} \cdot year^{-1}$ and 23.75 $gC \cdot m^{-2} \cdot year^{-1}$ for the EA and SA regions, respectively. It was found that the change of NPP-FV was totally different from that of T-NPP, with increments in all three regions after the urbanization. The magnitude of NPP-FV in the OC and EA regions is clearly higher than that in the SA region, due to the contribution of the indirect impact, and the decrease of T-NPP was mostly the result of the direct impact.

Since the urbanization has led to huge carbon sink losses in the Kunming region, it was necessary to analyze the most effective way to offset the changes by urban greening. During the urbanization process, about 104.76 km^2 of vegetated areas were replaced by other land covers, which was the major cause of the carbon loss. However, a much smaller area of urban greening is needed to compensate for this, because the NPP-FV has been improved due to the positive indirect impact. For the average of the whole region, the NPP-FV increased by 1.33 times after urbanization, which indicates that adding 75.36% of the vegetation area loss (78.94 km^2) would be enough to offset the carbon loss in the region. What is more, the vegetation demands vary with the different regions, because of the NPP-FV differences. As shown in Table S2, the minimum urban greening area would be required if all the vegetation was added in the OC region (61.77 km^2), due to the high NPP-FV in this region after urbanization. However, the area required amounts to 70.27% of the total OC region, so it would be impossible to convert this much area into vegetation, since this is a residential area. Converting the land in the EA region to vegetation would be ideal, because this would only require 24.46% of the EA region land surface (82.21 km^2). If the vegetated area was concentrated in the SA region, almost double the area of the OC region would be needed (100.81 km^2). In conclusion, it would be better to undertake the urban greening in an order of priority of OC, EA, and SA, in order to offset the carbon sink loss caused by urbanization. Undertaking rational urban greening in the OC area would be an ideal way to save on total land consumption and leave more land for human use.

4.3. Data uncertainty and future works

The major uncertainties of this study come from the applied NPP data and the land-cover series, so it is necessary to discuss these issues. The NPP estimated by the CASA model was employed to represent the vegetation growth status, but the input data and model applicability can greatly affect the results. As one of the most important inputs, the NDVI data were obtained by fusing multi-source remote sensing data,

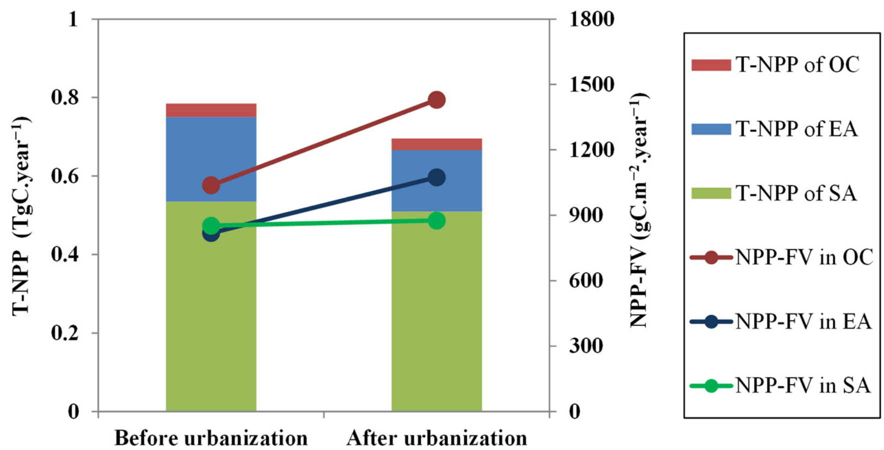

Fig. 7. Comparison of carbon budget and NPP-FV after urbanization in the different regions, where T-NPP denotes the total NPP in the region, NPP-FV denotes the actual NPP of unit full vegetation cover area, OC denotes the old city area, EA denotes the expansion area, and SA denotes the sub-urban area.

to combine the spatial resolution and long-time span characteristics from different sensors. The monthly total solar radiation was calculated based on the improved Yang hybrid model (YHM2), in order to reduce the interpolation error caused by inadequate data sites. Although the applicability of all the employed data has been proved, the data processes and the parameter value definition could bring some bias to the NPP results. For example, the values of maximum light use efficiency, which have been proved to vary in different species, were derived from the previous study of Zhu et al. (2007), but it would be much better to adjust this to be suitable for urban vegetation. The estimated NPP dataset shows good consistency with the field measurements ($r = 0.79$, $p < 0.01$) in the whole of Yunnan province, good accuracy also could be observed among different vegetation types with bias ranged from -5 gC·m^{-2}·year^{-1} to 74 gC·m^{-2}·year^{-1}. However, the reliability in the Kunming urban area has not yet been validated, due to the lack of field measurements. Thus, using the MODIS NPP product (MOD17A3) was an effective way to assess its accuracy, and the result indicated a good consistency in the inter-annual variation ($r = 0.83$, $p < 0.01$). The much lower value for the estimated NPP also agreed with the previous studies, which declared that the MODIS product overestimated NPP in low-productivity areas (Turner et al., 2006).

The land-cover data series could also bring uncertainty to the conclusions, because these data are the specific data used to evaluate the urbanization status. Due to the 30-m spatial resolution of the Landsat data, and the fact that only three classes (impervious surface, vegetation, bare soil) were considered, the overall classification accuracy was generally higher than 90%. However, the seasonal differences of the acquired data would also cause uncertainty, because the phenological difference of the vegetation in the different data would induce error when evaluating the vegetation cover in each year. Although all the classified Landsat images were selected as near as possible to the spring season, certain seasonal differences still existed. In order to further minimize the effects of the seasonal differences of the data, the separation of the direct and indirect impacts was based on the urban expansion intensity β. Due to the fact that β was defined as the fraction of impervious surface, this ignored the impact of the phenological differences of the vegetation.

In general, although there are some uncertainties in the employed data, we believe that the conclusions obtained in this study are credible and valuable. However, further efforts are still required for an in-depth exploration of the impact of urbanization on regional terrestrial ecosystems. First of all, this study only separated the impact of urbanization into two classes, so it would be meaningful to divide the indirect impact into more detailed classes. The direct impact in this study was defined as the change of vegetated area, but the changes of the vegetation species should also be included in further study. The indirect impact was made up of the effects of climate change and anthropogenic activities, and the impact of climate change covered the natural changes and urbanization-induced changes, such as the UHI effect, the urban rain island effect, and so on. The high-rise buildings caused by urbanization could also bring huge indirect impacts and alter the growth environment of vegetation. How to separate these different factors is an interesting direction for future work, and it will be of great significance in advancing our knowledge of urbanization and terrestrial ecosystems. Furthermore, the spatial resolution of the applied NPP data was 1 km. However, considering the complex land cover in urban area, even higher spatial resolution data (e.g., Landsat data at a 30-m spatial resolution) would be superior. It could not only obtain the detailed spatial heterogeneity in urban area, but also retrieve more accurate information of vegetation and urbanization (Chen, 1999). Although there exists trade-off between the spatial and temporal resolutions, combining multi-sensor information and data integration method should be an effective approach to break this limitation, and some researches have already studied the vegetation in urban at the Landsat scale based on it (Yan et al., 2018; Liu et al., 2018).

5. Conclusions

In this paper, the continuous direct and indirect impacts of urbanization on regional NPP have been analyzed from 1990 to 2014 for the city of Kunming, China. A 1-km long-term monthly NPP time series obtained by the fusion of multi-source data was applied, and the fine-resolution land-cover time-series data were derived from Landsat images. Based on the concept that the NPP of an urban pixel can be determined by the fraction of the vegetated area, the direct and indirect impacts in each year were separated and analyzed. The main conclusions can be summarized as follows:

1) The city of Kunming has suffered intense urbanization at an accelerating rate over the past 25 years, with an exponential increase in impervious surface coverage. Most of the urban sprawl has been concentrated in the EA region, whereas more urban greening than impervious surface increment has taken place in the OC region.
2) The direct and indirect impacts of urbanization on NPP were completely different, in both the values and variation trends. The direct impact became more and more negative over time, resulting in a decreased average NPP in the region. However, the indirect impact was positive and showed a logarithmic increase, which represented the improved growth status of vegetation in the urban area.
3) The inter-annual variation trend of the indirect impact (1.55 gC·m^{-2}·year^{-1}) in the urban area was higher than the NPP trend in the NA region (1.34 gC·m^{-2}·year^{-1}), which indicates that

urbanization has brought positive factors and has enhanced the vegetation growth. The positive indirect impact shows apparent spatial and temporal heterogeneity, with higher values in the OC region and the winter months. Considering the positive indirect impact, urban greening in the OC region would be the best way to offset the carbon sink loss caused by urbanization.

4) The correlation analysis indicated that temperature variation was the main driving force of the indirect impact, and it could explain the heterogeneity of the indirect impact. However, the correlations between NPP and climatic factors were completely different, which proved the necessity of separating the indirect impact from the direct impact.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2019.02.361.

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